NBER WORKING PAPER SERIES

PROSPECTIVE ANALYSIS OF A WAGE SUBSIDY FOR CAPE TOWN YOUTH

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Working Paper 17248
http://www.nber.org/papers/w17248

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2011

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NBER Working Paper No. 17248
July 2011
JEL No. J64,J68

ABSTRACT

Recognizing that a credible estimate of a wage subsidy'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 examine the impact of a wage subsidy, we find that a R1000/month wage subsidy paid to employers leads to an increase of R660 in mean accepted wages and a decrease of 15 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] One policy response being actively considered is an employer wage subsidy for young workers. 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 so the subsidy increases accepted wages and reduces the probability of lengthy unemployment spells. Specifically, we find that a R1000/month wage subsidy paid to employers leads to an increase of R660 in mean accepted wages and a decrease of 15 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 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

[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.

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), and Burns, Edwards and Pauw (2010).

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 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, 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 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

[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.

[3]See Magruder (2010) for a discussion of the extended consequences bargaining councils on wage setting.

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:

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

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.[5]

[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.

[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:

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. 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:[6]

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

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 $\theta = (q, \lambda, \sigma_\epsilon)$.[7] Note that

---

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

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

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

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 estimate the preferred version of the model using survey data on the reservation wage. Because the CAPS data has the rare advantage of self-reported reservation wages, 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.[8]

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

[8]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.

wage (Flinn and Heckman 1982, Eckstein and 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

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) 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 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 $N = 1,430$ 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

[9] Flinn and Heckman (1982) and Eckstein and 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.

[11] We define school exit as being out of school for at least 3 consecutive months. A related paper, Pugatch (2011) uses this data to investigate school re-enrollment.

12 months, while 42% of the sample is unemployed for at least one year. Observed search behavior appears low with 35% never searching since leaving school. Nonetheless, few youth 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.[12] Unlike many African economies, South Africa does not have a substantial informal sector. The mean accepted wage was 2486 rand and wages are measured in real South African rand per month (base month August 2002, at which time the South African rand/US dollar exchange rate was 10.59). Table 1 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 2 presents unemployment durations and rates by observable characteristics. The data reveal 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 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]

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 1 showed that 24% of those with completed

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

[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 for work prior to obtaining work, and therefore exclude them from the "never searched" group so as not to bias results.

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

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. Table 3 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 youth 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.

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-level fixed effects to account for time-invariant individual heterogeneity, and we find no evidence of declining reservation wages. We conclude that the assumption of constant reservation wages is plausible.[15]

[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 Berg 1990) to evolve over time in a known fashion is at odds with the South African experience.

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 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) 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 may account for the increasing density in the far 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 next 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 observed heterogeneity by modeling the job arrival rate and the wage offer as log linear functions of a parsimonious set of covariates: indicator variables for black, coloured, high school graduate, at least some college, high ability,[18] and previous work experience; the omitted group is low-ability whites 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.[19]

[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 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.

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

[19]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.

As noted above, the reservation wage plays a key role in identification of the model. We incorporate the reservation wage into our model first in a base case approach and then using two alternative approaches.

4.1 Base Case Estimates

In the base case, 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 4.

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.[20] 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 approximately 80% and 40%) lower, respectively, than those for whites. High school graduation and post-secondary schooling generate large 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%.

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 marginal effects in log points, as before. The estimated baseline wage offer, at R710, is quite low relative to the mean accepted wage of R2,486.[21] Not surprisingly, the model predicts that only 29% of wage offers are accepted.[22] As with the offer arrival rate, the estimates imply considerable

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

[21] 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.

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

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 R513, while the latter receives offers more than four times as large, at R2,113. The estimated measurement error standard deviation, σ_ϵ, implies that measurement error accounts for 27% of the standard deviation in accepted wages.[23]

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 the last paragraph of section 2.2. We denote this measure as w^*_{MLE}.[24] 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 impact of the wage subsidy varies depending on which measure of the reservation wage is used.

Table 5 presents parameter estimates for each alternative. The first column repeats the base case estimates for comparison while column 2 reports results with w_{q_5} and column 3 reports estimates

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

[24] 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^*.

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 .27, versus .07 and .15 under w_{q_5} 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 selective 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 R1,445 in the model with w_{q_5} (Table 5, column 2) is more than double that of the model with w^*. The baseline offer of R899 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_{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 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 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 w^* begs the question, "If the South African youth labor market is so bad, why are youth turning down so many jobs?" Our answer is that it is unlikely that youth 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 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.

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, 69 percent of actual unemployment spells exceed 3 months while the model, for each treatment of the reservation wage, predicts that 75 percent of the spells would exceed 3 months. The model almost exactly predicts the fraction of spells exceeding 12 months (42 percent) and 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 R2486 while, when we use the reported reservation wages, w^*, the model predicts a mean accepted wage of R2346. 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.[25] 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, comparing entire distributions of outcomes.

[25] Appendix C describes details of these tests.

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.

As government in South Africa contemplates responses to youth unemployment, a wage subsidy is being actively considered. In his 2010 budget speech, Finance Minister Pravin Gordhan stated:[26]

> Many South Africans, speaking of their own experiences on the streets of our cities, at factory gates and in rural communities, have urged us to take steps to make it easier for young people to find work. Labour market data confirm that employers are reluctant to hire inexperienced work-seekers, while school-leavers lack basic workplace competencies. Furthermore, our bargaining arrangements push up entry level wages, pricing out inexperienced work-seekers.
>
> Under the leadership of the Department of Labour, initiatives are in progress to improve information services to help young people access jobs and training opportunities. We propose to support these reforms through a subsidy to employers that will lower the cost of hiring young people without work experience.

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.

[26]The entire National Budget Speech is found at Gordhan (2010).

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 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.[27] The subsidy $s = 0$ corresponds to the baseline estimates discussed in the preceding sections, and s increases to R1,000 in increments of 100 along the horizontal axis. (To put the size of the subsidy in context, note that the mean wage in the sample is about R2486.) The top panel shows that the reservation wage increases monotonically with the subsidy and that the relationship is close to linear. A R1000 subsidy increases the reservation wage by about R660 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 R1000 subsidy increases

[27] 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}.

the mean accepted wage by about R660 (and recall this is assuming that the subsidy is fully passed through to the wage offer distribution).[28] Hence, only about 66% 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 66% 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 reported reservation wages, w^* (as opposed to w_{q5} or w^*_{MLE}), the probability of accepting a job offer increases from .30 to about .44 with a subsidy of R1000. 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 reported reservation wages, w^*, the fraction of youth who report an unemployment spell of 12 months falls from about 42% with no subsidy to about 27% with a R1000 subsidy. A 15 point reduction in long term unemployment strikes us as quite sizeable. The reduction is close to 10 percentage points when we estimate the model without using reservation wages inferred from the 5th percentile of accepted wages. 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 reported reservation wages has 25% of individuals reporting a 24 month period of unemployment, and this falls to about 10% with a R1000 wage subsidy.

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 66% 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

[28]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.

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.

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.

6 Conclusion

Persistently high youth unemployment is one of the most pressing problems in South Africa. The South African government has proposed an employer wage subsidy to address the issue. 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 R1000/month wage subsidy paid to employers leads to more frequent job offer acceptances, increased accepted wages and substantial declines in even long term unemployment.

This paper is hardly the final word on this question but rather represents an initial examination of an important policy option.

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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 Definitions

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

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.[29] 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:

$$1 = \hat{m}_i' \delta + \hat{s}_i' \gamma + u_i$$
$$1 = \hat{m}_i' \delta + u_i$$

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).[30]

[29] 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.

[30] 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
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 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. Statistics calculated using sample weights ($weightyr$).

Table 2: Unemployment, by observable characteristics

	First UE spell	UE spell$\geq$1yr	UE spell$\geq$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:					
$\leq$18	13.9	0.50	0.35	0.59	0.33
19-22	10.9	0.39	0.25	0.50	0.20
$\geq$23	7.4	0.27	0.18	0.34	0.11
schooling:					
$\leq$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: Reservation wage regressions

	(1) w_i^*	(2) 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 4: 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 5: Parameter estimates, using alternate reservation wage measures

Reservation wage	(1) w^*	(2) w_{q5}	(3) 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 6: Empirical and predicted unemployment survivor functions

	$\mathbf{Pr}(d \geq d_0)$			
	(1)	(2)	(3)	(4)
	empirical	w^*	w_{q5}	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		424.7	399.3	430.7
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_{q5}	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		221.7	204.0	196.8
p-value		0.00	0.00	0.00

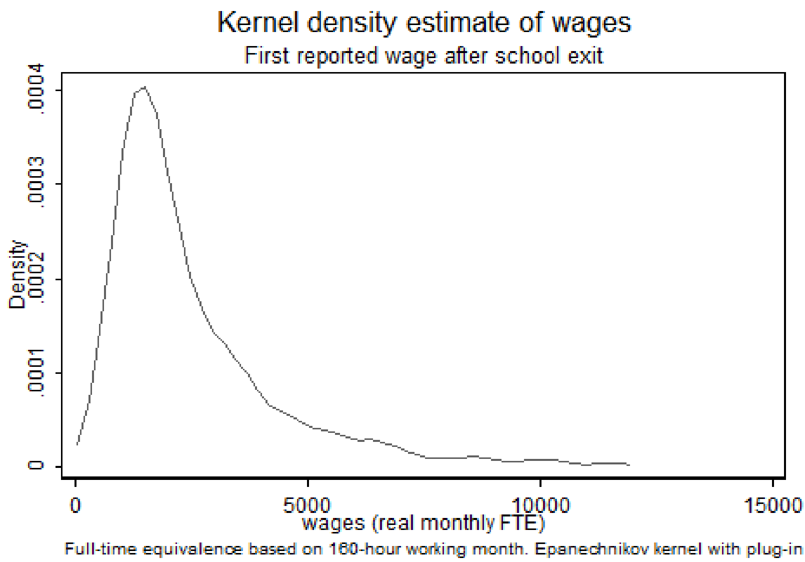
Each cell reports corresponding moment or quantile of observed accepted wages for empirical wage distribution (column 1) and predicted wage distribution by reservation wage input used in model estimation (columns 2-4). χ^2 statistic is from auxiliary regression of ones on sample moments; statistic is 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.

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)

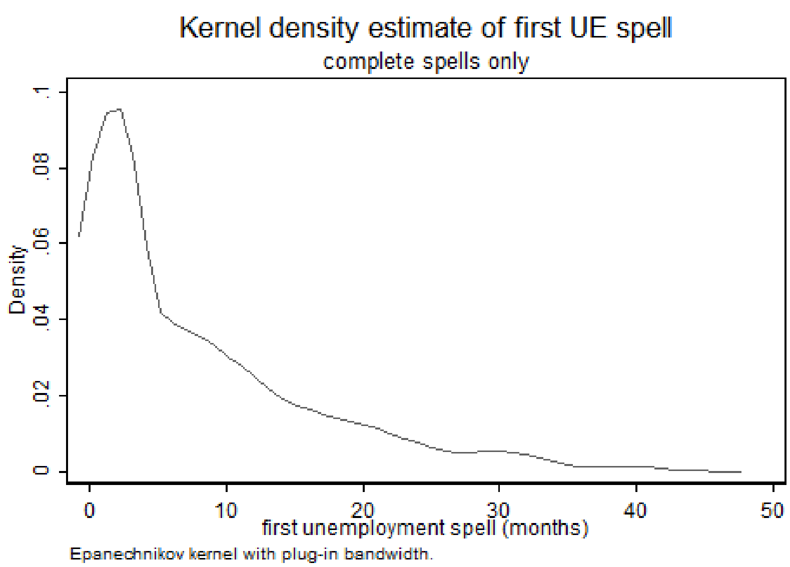
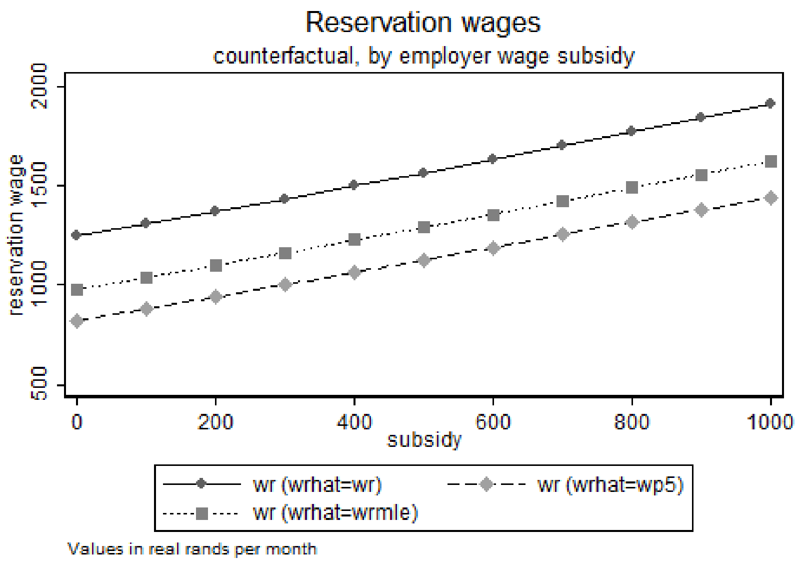


Figure 3: Reservation wages and accepted wages under employer wage subsidy

(a)



(b)

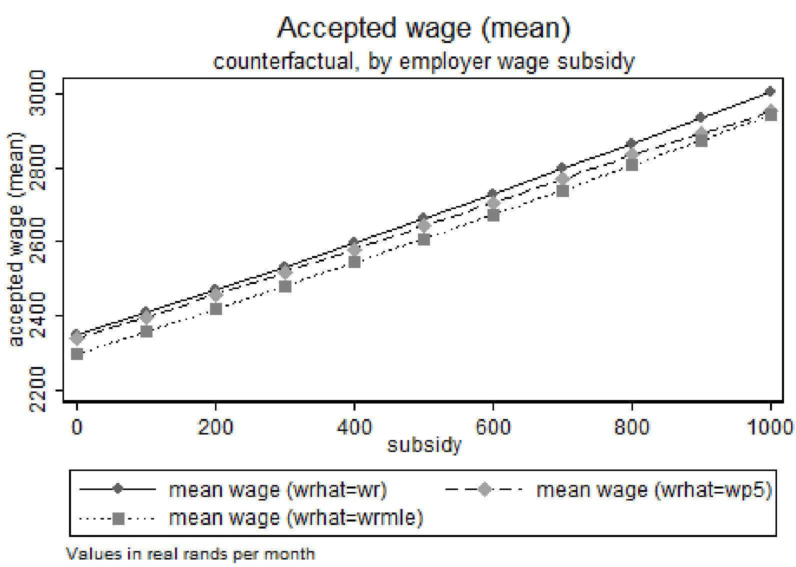


Figure 4: Probability of offer acceptance under employer wage subsidy

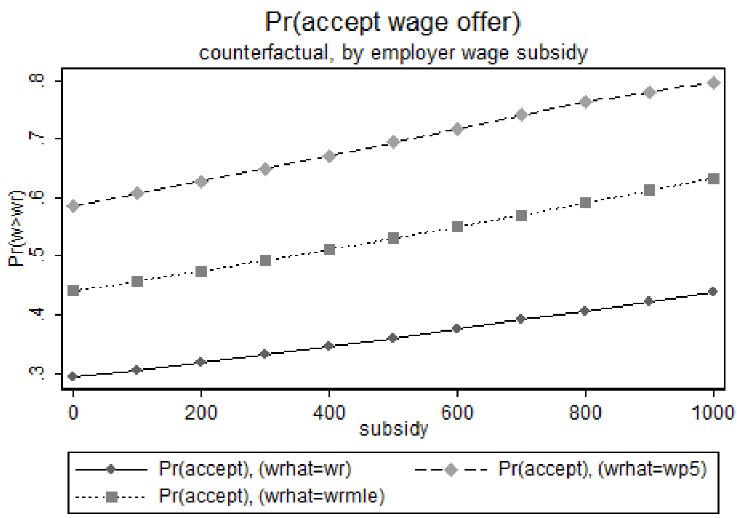
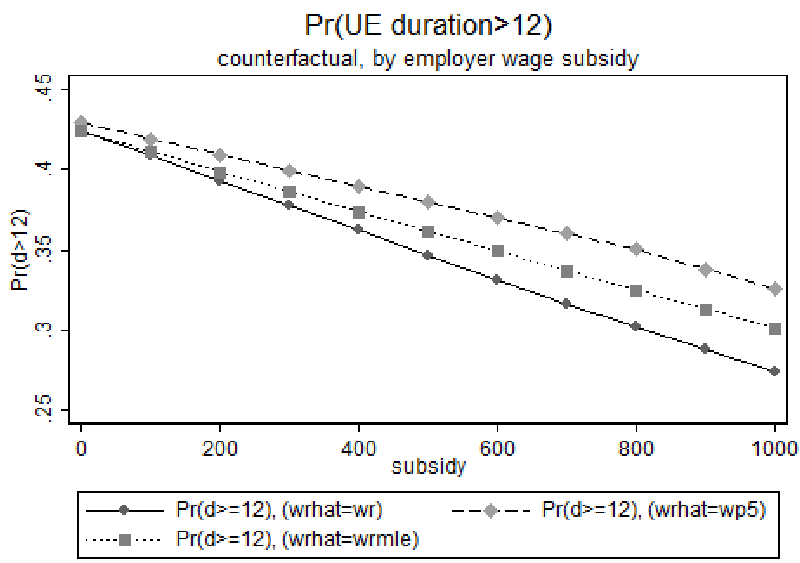


Figure 5: Unemployment survivor function under employer wage subsidy: 12 and 24-month UE spell

(a)



(b)