

**THE IMPACT OF GENDER DISCRIMINATION ON THE JOB SEARCH
STRATEGIES OF REDEPLOYED PUBLIC SECTOR WORKERS**

Bradford Mills

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1. INTRODUCTION

Gender discrimination in the wage sector is common in the labor markets of developing countries. At the same time, wage employment opportunities in the public sector are generally believed to be more equitably distributed than those in the private sector. This raises the concern that women who leave the public sector workforce as part of downsizing efforts will have more difficulty than their male counterparts in finding new private-sector positions. This paper examines whether differential access by gender to wage-sector employment opportunities leads to different durations and outcomes of job search, for wage- and nonwage-sector positions, after departure from the public sector. The impacts of wage-sector employment premiums and public-sector severance compensation schemes on job-search outcomes are also examined.

The next section of the paper develops a model of employment search in a segmented labor market following public sector job loss. The model assumes that nonwage employment is a second best, but commonly pursued, employment option, and that gender discrimination dictates that fewer females will receive wage-employment offers during their job searches. Section 3 presents a semiparametric estimator of the duration of unemployment following public-sector job loss, when the probabilities of exits into the wage and nonwage sectors are correlated. The data set of former public-sector workers in Conakry, the capital of Guinea, is discussed in Section 4. Section 5 presents the estimated results of the model and Section 6 discusses the implications of the results. Section 7 reviews the salient findings of the paper.

2. THE MODEL

Most empirical models of job search have examined departures from unemployment into a single employment state.¹ In these models job searchers in any period are typically assumed to face a fixed probability of receiving a wage offer and a distribution of possible levels of remuneration accompanying the offer. However, in the labor markets of developing countries, nonwage activities often comprise the majority of employment opportunities. The mechanisms that generate wage-sector opportunities differ significantly from those generating opportunities in the nonwage sector. To account for these factors, I have developed a job-search model that accounts for the distinct employment opportunities available in the wage and nonwage sectors.

Wage-sector positions are assumed to be preferred because they offer a compensation premium, greater stability in employment and income, or greater access to in-kind or other benefits.² Individuals, therefore, willingly undergo spells of unemployment in the search for wage-sector positions, instead of taking more readily available, but less rewarding, nonwage sector opportunities. Several theoretical models have been developed to demonstrate mechanisms that restrict the supply of wage offers and maintain a premium for wage-sector positions. Possible mechanisms include incomplete information, shirking, and social pressures from family, ethnic group, existing employees, or other social cohorts (Akerloff 1984). The model assumes that restrictions on the demand for wage labor cause wage offers to all sectors to be generated through a Poisson process. An additional assumption, that gender discrimination causes the frequency of arrival of offers to be lower for females than males, will be empirically tested.

The lack of access to credit and to information on enterprise possibilities is a barrier to entry into the nonwage sector. However, this barrier inhibits entry by lowering the expected returns to nonwage employment. Thus, the set of expected nonwage opportunities is assumed to be fixed over time and the opportunities themselves are immediately available to job searchers.³ Observed unemployment then arises from job searches for preferred, stochastically generated, wage-sector opportunities.

To isolate the impact of discrimination on job search decisions, individuals are assumed to have linear utility functions and only two periods remaining on

¹ For a review of the theory of basic models of job search, see Lippman and McCall (1976).

² Extensive discussions with former public sector workers in Conakry, Guinea support the validity of this assumption in this case.

³ Barriers to nonwage employment may fluctuate randomly over time, thus changing expected returns to nonwage employment. However, the frequency of new nonwage opportunities is expected to be limited relative to wage opportunities.

their earnings or search horizons when they commence their job search.⁴ Job search within each period is then a two-step process. First, the individual must decide whether to accept available nonwage employment or to remain unemployed while searching for wage-sector employment. Second, if search for wage employment is chosen, the person must decide whether to accept any generated wage offers.

LABOR MARKET DECISIONS IN PERIOD T

Let T indicate the beginning of the last period of the individuals employment horizon. If the individual is unemployed at T , once he or she commits to search for wage employment, there are no other options for the period. Therefore, if a wage offer, $w(T)$, is received from wage offer distribution function $W(T)$, it will be accepted, since the reservation wage is equal to the discounted expected value of the next period's options. In this case there are no next-period options and the reservation wage is zero. The choice can be expressed:

$$\max \{w(T), 0\}. \quad (2.1)$$

The corresponding decision to search for wage employment or accept nonwage employment can be written as a comparison between the expected value of search and the expected returns to nonwage employment:

$$\max \left\{ \lambda \int_0^{\infty} w_T f(w_T) dw_T, E[s_T] \right\}, \quad (2.2)$$

where λ is the probability of receiving a wage offer in period T , $f(w_T)$ is the probability density function of wage offers, and $E[s_T]$ is the expected returns to nonwage employment in period T .

LABOR MARKET DECISIONS IN PERIOD $T-1$

Let $T-1$ indicate the beginning of the next to last period of the search horizon. In period $T-1$ the individual, if he or she decides to search, has a non-zero reservation wage because the option exists to wait until period T and then to choose from available options, discounted at rate δ to the present.

⁴ A finite search horizon can be justified either by age restrictions on employment or limits on the household reserves that are used to finance consumption during job search.

$$\max \{ (1 + \delta) w_{T-1}, \delta \max \{ \lambda \int_0^{\infty} w_T F(w_T) dw_T, E[s_T] \} \}. \quad (2.3)$$

Thus, the wage offer is accepted in $T-1$ only if its value is larger than the probability of receiving a wage offer in T , times the discounted expected value of the offer:

$$w_{T-1} \geq \frac{\delta}{(1 + \delta)} \max \{ \lambda \int_0^{\infty} w_T f(w_T) dw_T, E[s_T] \}. \quad (2.4)$$

Correspondingly, the expected return to searching in period $T-1$ can be written as the sum of three terms: 1) the probability of receiving an offer in $T-1$, times the discounted expected value of the offer, given that expression 2.4 holds, and that the offer is accepted; 2) the probability of receiving a wage offer in $T-1$ below the reservation value for acceptance times the discounted expected value of the options available in period T and 3) the probability of not receiving an offer in $T-1$ times the expected value of the options available in period T .

$$\begin{aligned} & \left[\lambda \int_H^{\infty} (1 + \delta) w_{T-1} f(w_{T-1}) dw_{T-1} \right] \\ & + \lambda \int_0^H f(w_{T-1}) dw_{T-1} * \delta \max \{ \lambda \int_0^{\infty} w_T f(w_T) dw_T, E[s_T] \} \\ & + (1 - \lambda) \delta \max \{ \lambda \int_0^{\infty} w_T f(w_T) dw_T, E[s_T] \}; \end{aligned} \quad (5)$$

where

$$H = \delta / (1 + \delta) \max \{ \lambda \int_0^{\infty} w_T f(w_T) dw_T, E[s_T] \}. \quad (2.5)$$

The expected value of nonwage employment in period $T-1$ is simply:

$$(1 + \delta) E[s_{T-1}]. \quad (2.6)$$

Before examining the impact of gender discrimination on job search decisions, it is important to note that the model allows for the observed stream of departures from unemployment to both the wage and nonwage sectors. As individuals move through time toward the end of their earnings horizons, the expected value of search decreases faster than the expected value of nonwage employment (for proof, see Appendix 1). Thus, despite a constant expected value

of nonwage employment across periods, in each period some individuals can be expected to give up their search for wage-sector employment and enter the nonwage sector.

THE IMPACT OF GENDER DISCRIMINATION

The impact of gender discrimination on the probability of entering both wage- and nonwage-sector employment can be shown by examining the impact of a change in the rate of wage offers on the components of the expression for the expected value of search in period $T-1$.

Proposition: If the rate of generation of wage offers is lower for females than for males ($\lambda_f < \lambda_m$), then the probability of exit from unemployment to the nonwage sector in each period (the hazard rate) will be higher for females than males. However, the effect on the hazard rate of departure into the wage sector is ambiguous.

Individuals exit unemployment into the nonwage sector when the expected value of nonwage employment (expression 2.6) is greater than the expected value of searching (expression 2.5). Since wage-sector discrimination does not affect the expected value of nonwage employment, showing that the expected value of searching for females is lower than the value for males in each period, *ceteris paribus*, is sufficient to prove that the probability of entering the nonwage sector is higher for females than males for each period.

In a comparison of the expected values of search for males and females, the reservation level for accepting a wage offer for females in period $T-1$ is either equal to or lower than that for males, depending on whether search or nonwage employment yields the maximum expected value in the last period. If the expected value of nonwage employment is larger for both males and females in period T , then clearly the expected value of search must be lower for females, since the lower rate of wage offers increases the probability of not receiving a wage offer in $T-1$ and accepting nonwage employment in period T .

If searching for wage employment yields a greater expected value in the last period for both males and females, the expected value of search in $T-1$ is still unambiguously lower for females. Since the reservation level for acceptance of a wage offer for females is now lower than that for males:

$$\delta/(1 + \delta) \{ \lambda_f \int_0^{\infty} w_T f(w_T) dw_T \} < \delta/(1 + \delta) \{ \lambda_m \int_0^{\infty} w_T f(w_T) dw_T \}, \quad (2.7)$$

it is necessary to carefully compare the three terms in expression 2.5 to evaluate the relative magnitudes of the expected value of search by gender.

The first term in expression 2.5 reveals that the probability of receiving offers above or equal to the male reservation wage is smaller for females. There is also a positive probability that a wage offer that would be rejected by males would be accepted by females, because of their lower reservation level for acceptance of wage offers. Term two shows that there is a lower probability that a wage offer is received and rejected by females than males. However, the expected value of the next period gained from this outcome is lower for females. Finally, term three shows that females have higher probability of not receiving a wage offer and obtaining only the expected value of the next periods option, which is again lower for females than males. Clearly, from the combination of the three terms females have less chance of receiving a wage offer equal to, or greater than, the male reservation-acceptance level and a greater probability of not receiving an offer and ending up with the discounted expected value of the next periods option. Thus, the expected value of search in $T-1$ is lower for females than males.

In a third feasible case, females chose nonwage employment in the last period while males chose to search for wage employment.⁵ The analysis is essentially the same as for the second case. Female reservation wages are again lower than for males. Thus, the expected value of search is again lower for females than for males and females are more likely to accept nonwage employment in any period.

Conversely, the impact of gender discrimination on the probability of entering the wage sector in any time period is ambiguous. It was shown above that females are less likely to search for wage-sector employment. If search does occur, they are less likely to receive wage offers. However, females have a lower reservation acceptance level for wage offers and are, therefore, more likely to accept a given wage offer.

THE IMPACT OF OTHER VARIABLES

Several other variables, including the duration of unemployment, are important to job search decisions, and are included in the empirical model. Perhaps the variable most important in job-search decisions is the size of the premium for wage-sector employment.

The impact of a wage premium on job-search decisions is similar in principle to the impact of gender discrimination. Assume that an increase in the wage premium results from an upward shift in the wage distribution. A second wage-offer distribution with probability density function $g(w)$ increases the probability of higher wage offers, such that $G(w) < F(w)$ for all w and that the

⁵ Females searching and males accepting non-wage employment in the last period is not a feasible case, since the value of search can not be higher for females than males in the last period.

conditional expected wage under $G(w)$ is greater than under $F(w)$ for all reservation wages. Clearly the expected value of the last period wage offer is larger under the new distribution.

Again, similar to the case of gender discrimination, the three possible cases all show a negative relationship between the size of the wage premium and the probability of accepting nonwage employment in any period. In case one, the expected value of nonwage employment is greater than that of searching for both wage distributions in the last period. Clearly the increased probability of larger wage offers increases the expected value of search under the new wage distribution. In case two, search is undertaken for both wage distributions in the last period. Under the new distribution, the higher expected value of wage employment in period T encourages person to reject wage offers they would have previously accepted in period $T-1$. Thus, an increase in the reservation level for the acceptance of wage offers, combined with the higher frequency of better wage offers, causes an increase in the expected returns to search, which decreases the probability of nonwage employment acceptance in any period. Finally, under case three the individual with the higher wage-offer distribution searches wage employment in the last period while the individual with the lower distribution accepts nonwage employment. The analysis is essentially the same as in case two, and the higher premium again results in a lower probability that the individual will accept nonwage employment in period $T-1$.

Conversely, the impact of increasing the premium to wage-sector employment on wage-sector transitions is ambiguous. Clearly individuals are more likely to search for wage employment when the premium for wage-sector employment is high. However, because both the wage-offer distribution and the reservation level for acceptance of wage offers for wage-sector employment change, without additional knowledge of the functional form of the wage-density function, it is not possible to theoretically sign the impact of increasing the wage-sector premium on the intensity of transition into the wage sector.

The impact of severance payments on job-search decisions is also examined in the empirical model. Several studies have shown that unemployment insurance has a positive impact on the duration of unemployment. This effect is due, in part, to the lower net present value of job offers when unemployment benefits are lost upon the acceptance of new employment. In the case of severance payments, the stream of benefits continues after employment is accepted. Thus, severance payments have no direct impact on the value of job offers.

However, severance pay may still impact on the probability of accepting wage and nonwage employment. Job searchers may face a limit on the amount of time that can be spent searching before savings are exhausted and any available employment opportunity must be accepted. Severance payments then serve to extend the time available for job search and decrease the probability of wage-employment acceptance in any period. The same effect holds for the decision to accept nonwage sector positions. However, severance payments may also ease capital constraints to nonwage employment opportunities; this in turn increases the

probability that the individual will enter the nonwage sector. Thus, the net impact of severance payments on the probability of acceptance of nonwage sector positions is ambiguous.

The age of the individual at the date of departure from the public sector is also included in the empirical model. Appendix 1 shows that as individuals approach the end of their earnings horizons, they become less likely to search for wage-sector employment. Since older individuals are expected to be closer to the end of their earnings horizon, they should be more likely enter nonwage employment. However, it should be noted that the magnitude of this effect can be expected to be very small in a cohort of predominantly middle-age individuals.

Finally, a dummy variable for post-1986 redeployments is included in the empirical model, to control for the impact of the economic reform program in Guinea. One of the goals of the economic reform program was to liberalize markets and increase private-sector investment. Whether this would result in a greater demand for wage or nonwage sector employment is not clear, a priori, and will be tested empirically.

3. THE STATISTICAL MODEL

This section specifies semiparametric estimators when both single and dual (wage and nonwage sectors) exit states from unemployment are possible. The per-period probabilities of departure developed in the theoretical model can be expressed by a basic hazard function that allows for the presence of covariates:

$$\theta(t;x) = \lim_{dt \rightarrow 0} \frac{P(t \leq \tau \leq t + dt \mid \tau \geq t, x)}{dt}; \quad (3.1)$$

where $\theta(t;x)$ is the hazard for period t , τ is the actual departure time, and x is a matrix of covariates believed to be related to departure times. Thus $\theta(t;x)$ is the proportion of individuals, homogeneous in x , who leave in the short time interval t to $t + dt$.

To empirically estimate the hazard function, a specific functional form must be specified. Unfortunately, most common parametric forms for hazard functions impose strong restrictions on the movements of hazard rates through time. Thus, without prior information about the hazard's time dependence, it is likely that the imposition of an arbitrary functional form will lead to model misspecification. Alternatively, the hazard may be specified as a function of temporally variable and covariate components:

$$\theta(t;x_i) = \theta_0(t) \exp[-x_i B]; \quad (3.2)$$

where $\theta_0(t)$ is the time-dependent baseline hazard, X_i is a vector of covariates of individual i , and B is a vector of covariate parameter estimates.

Based on this specification of the hazard function, Han and Hausman (1990) develop a semiparametric estimator for single- and dual-risk cases. The estimator is semiparametric because the baseline hazard is assumed to be constant within the discrete time units into which continuous-duration data are grouped. These baseline hazard constants are then estimated together with the covariate parameter vector. This approach has several advantages in comparison to the partial likelihood competing risk approach developed by Cox (1975), which integrates the baseline hazard from the likelihood function. First, the approach allows for the presence of grouped data, common in economic duration studies, without utilizing ad hoc tie-breaking procedures. Second, the approach explicitly estimates a piecewise linear approximation of the underlying hazard. Finally, in the dual-risk case, the approach allows for correlation between risks.⁶

⁶ Most previous estimators of multiple departures have assumed either that the stochastic disturbances of the exit states are independent, and hence estimated independent standard-duration models for each exit state (Katz 1986), or allowed for correlation in stochastic disturbances by imposing strong parametric assumptions on the form of hazards (Diamond and Hausman 1984).

Let ε_i be the logarithm of the integrated hazard in equation 3.2.

$$\varepsilon_i = \log \int_0^{t_i} \theta_0(s) ds - X_i B. \quad (3.3)$$

For the single-risk case, it can be shown that ε_i takes an extreme value distribution.⁷

If the period intervals are ordered in time as $c = 0, 1 \dots C$ and $\log \int_0^c \theta_0(s) ds = \alpha_c$, then the probability of departure from unemployment in the interval $[c - 1, c)$ can be expressed as:

$$\int_{\alpha_{c-1} - X, B}^{\alpha_c - X, B} f(\varepsilon) d\varepsilon. \quad (3.4)$$

The corresponding log-likelihood function for the single-risk case takes the form:

$$\log L = \sum_{i=1}^N \sum_{c=1}^C y_{ic} \log \int_{\alpha_{c-1} - X, B}^{\alpha_c - X, B} f(\varepsilon) d\varepsilon; \quad (3.5)$$

where y_{ic} is a dummy variable for the period of departure.

To specify the dual-risk model in the presence of discrete data, let $t_1^*, t_2^* \geq 0$ be latent random variables for departure times into the wage- and nonwage employment sectors. The t 's are latent variables, because at least one and possibly both departure times are not observed. If a redeployee departs from unemployment for wage-sector employment, his or her time to departure into nonwage employment is unobserved. Further, it is possible for departure times into both the wage and nonwage sectors to be unobserved if the individual remains unemployed through the end of the periods within which data are recorded.

As functions of the latent departure times, α_t^1 and α_t^2 can be specified as:

$$\begin{aligned} \alpha_t^1 &= X_1 B_1 + \varepsilon_1, \\ \alpha_t^2 &= X_2 B_2 + \varepsilon_2. \end{aligned} \quad (3.6)$$

⁷ For a more complete discussion of the statistical properties of the integrated hazard, see Lancaster (1990, Section 4 of Chapter 1).

The probability density functions of the logarithms of the integrated hazards can again be expressed as extreme value distributions:

$$\begin{aligned}\varepsilon_1 &= -\log \int_0^{t_1} \theta_0(s) ds - \chi B_1; \\ \varepsilon_2 &= -\log \int_0^{t_2} \theta_0(s) ds - \chi B_2;\end{aligned}\tag{3.7}$$

where $\alpha_{t_1}^1 = -\log \int_0^{t_1} \theta_0(s) ds$ and $\alpha_{t_2}^2 = -\log \int_0^{t_2} \theta_0(s) ds$.

When departure to wage employment occurs in the interval $[c-1, c)$, so that $t_1 = \min(t_1, t_2)$, the probability of this outcome is:

$$\int_{\alpha_{t_1-1}^1 - \chi B_1}^{\alpha_{t_1}^1 - \chi B_1} \int_{\mu(\varepsilon_1)}^{\infty} f(\varepsilon_1, \varepsilon_2) d\varepsilon_2 d\varepsilon_1\tag{3.8}$$

where $\mu(\varepsilon_1)$ is such that the implied time to departure from nonwage employment is greater than wage employment, given ε_1 , and that $f(\varepsilon_1, \varepsilon_2)$ is an extreme-value probability-density function that allows for interdependence among stochastic disturbances.

If the integrated hazard is linear within the period intervals, it is straightforward to solve $\mu(\varepsilon_1)$ and $\mu(\varepsilon_2)$ for wage and nonwage departures, respectively.⁸ The corresponding likelihood function for both wage and nonwage sector departures is then expressed as:

$$\begin{aligned}\text{Log } L &= \sum_{i=1}^N \sum_{c=1}^C y_{ic} \left\{ (1-d_i) \log \int_{\alpha_{t_{i,c-1}}^1 - \chi B_1}^{\alpha_{t_{i,c}}^1 - \chi B_1} \int_{[\alpha_{t_{i,c-1}}^2 - \chi B_2] + h_1} f(\varepsilon_1, \varepsilon_2) d\varepsilon_2 d\varepsilon_1 \right. \\ &\quad \left. + d_i \log \int_{\alpha_{t_{i,c-1}}^2 - \chi B_2}^{\alpha_{t_{i,c}}^2 - \chi B_2} \int_{[\alpha_{t_{i,c-1}}^1 - \chi B_1] + h_2} f(\varepsilon_1, \varepsilon_2) d\varepsilon_1 d\varepsilon_2 \right\},\end{aligned}\tag{3.9}$$

where

⁸ This is equivalent to the assumption of constant baseline hazards within time intervals.

$$\begin{aligned} \infty < \alpha_1^1 < \alpha_2^1 < \dots < \alpha_c^1 < \infty, \\ \infty < \alpha_1^2 < \alpha_2^2 < \dots < \alpha_c^2 < \infty, \end{aligned}$$

$$h_1 = [(\varepsilon_1 - (\alpha_{c-1}^1 - X_{11}\beta_1)) / \gamma_c]$$

$$h_2 = [(\varepsilon_2 - (\alpha_{c-1}^2 - X_{21}\beta_2)) / \gamma_c]$$

and

$$\gamma_c = (\alpha_c^2 - \alpha_{c-1}^2) / (\alpha_c^1 - \alpha_{c-1}^1) \text{ for } c=2, \dots, C-1 \text{ with } \gamma_1 = \gamma_c = 1.$$

In addition d_i is a dummy variable for the state into which departure occurs.

For estimation purposes the extreme-value functions in the dual-risk estimator can be approximated as bivariate normal distributions. While the normal distribution does not follow directly from the proportional hazard specification,⁹ it provides a very close approximation of the extreme value distribution.

⁹ For a comparison of the performance of the single-risk estimator with extreme-value and normal distributions, see Han and Hausman (1990).

4. THE DATA

The data used in this study is from the Cornell Food and Nutrition Policy Program panel survey of 1,728 households in Conakry, Guinea. This sample contains two observations, exactly one year apart, of all household consumption, income, and health activities. From this sample, a survey of the subsample of individuals who were retrenched and/or left a public-sector job between 1979 and the first round of the survey in 1990-1991 was conducted. The subsample comprised of all the individuals initially surveyed who were (1) currently unemployed and had previously held a job in the public sector; (2) currently employed in either the public or private sector and who indicated they had left the public sector for an extended period of time in the last decade; and (3) currently employed in the public sector, but transferred from one public-sector position to another without a long spell of unemployment due to the government retrenchment program.

The supplemental "retrenchment" survey was administered to the subsample to collect specific information on labor history, including date of exit of the public sector, duration of unemployment accompanying the exit, compensation after exit, and new sector entered after exit. Table 1 presents the prevalence of spells of unemployment, by yearly groupings, for individuals eventually accepting wage and nonwage employment, or who were still actively seeking employment when the survey ended. Note that the number of exits into both states decreased over time, while the number of censored observations increased. This reflects the fact that some individuals left the public sector during the peak retrenchment period of 1985-1987 and were unable to find other employment before the retrenchment survey of 1992.

Figure 1 shows the Kaplan-Meier estimates of the nonparametric hazard functions for combined wage and nonwage sector exits.¹⁰ The single-risk hazard function estimates suggest that over 30 percent of redeployees who search for employment find it within a year of departure from the public sector, while only about 10 percent who remain unemployed at one year find employment within two years of leaving the public sector. The data then suggest that from the second year up until the seventh year after the departure from the public sector, the rate of exit from unemployment remains fairly constant, and that about 20 percent of redeployees who remain unemployed at the beginning of each year find employment within the ensuing year.¹¹

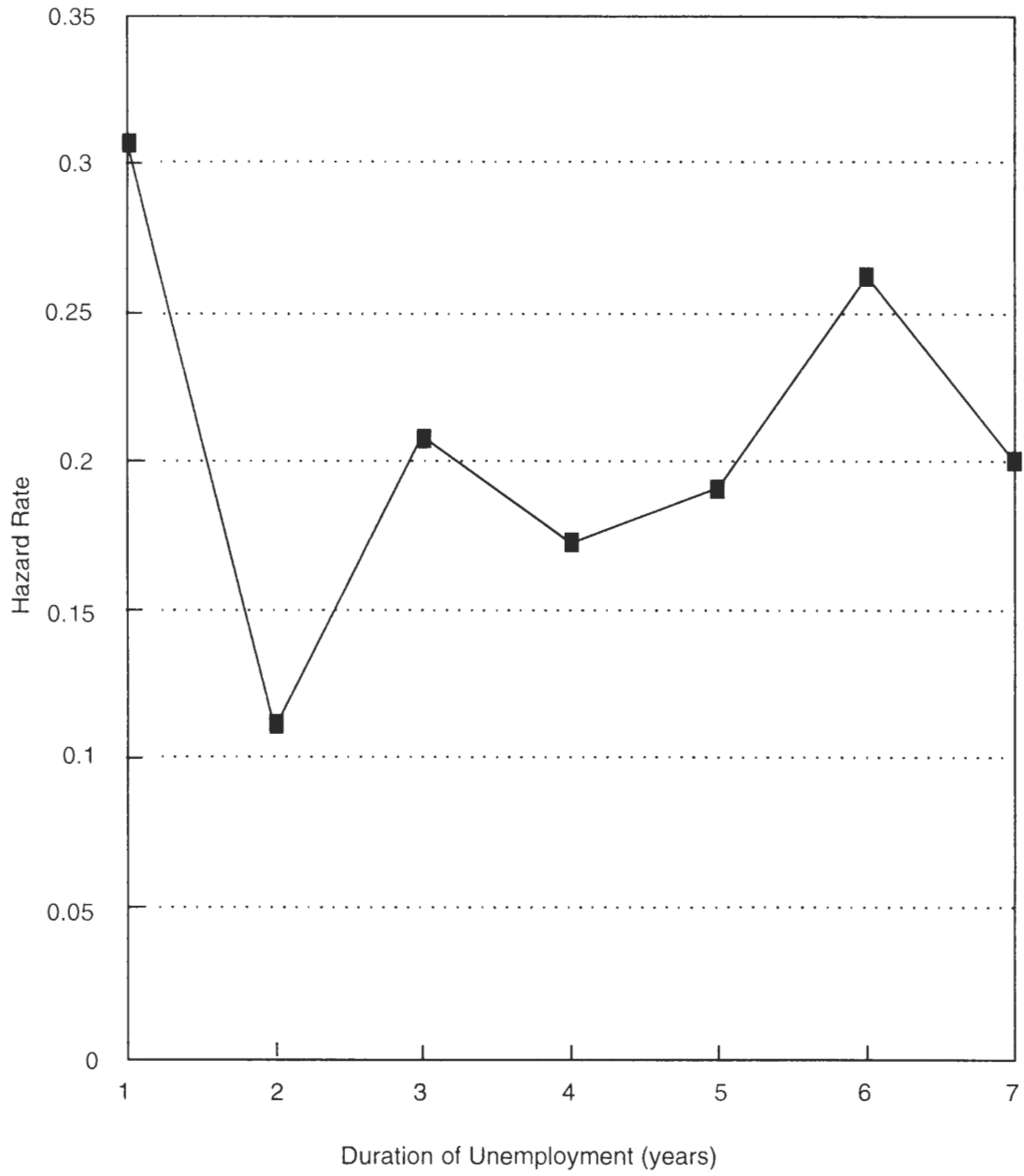
¹⁰ The Kaplan-Meier estimator is simply calculated as the number of exits in the period divided by the population unemployed at the beginning of the period minus censored observations within the period.

¹¹ Hazard function estimates are not reported for unemployment durations of seven years or more due to the limited number of uncensored observations.

Table 1 — Duration to Departure from Unemployment: Redeployed Public Sector Workers in Conakry, Guinea

Duration (Years)	Nonwage Employment	Wage Employment	Censored	Total
< 1	21	25	4	50
2	8	3	5	16
3	5	13	1	19
4	1	10	3	14
5	2	7	5	14
6	3	5	9	17
7	1	2	19	22
Total	41	65	46	152

Figure 1 - Nonparametric Hazard Rates for All Individuals Leaving Unemployment



However, the nonparametric estimates of the hazard functions look very different for separate departures to the wage and nonwage sectors (Figure 2).¹² After two years of unemployment, uptake into the wage sector appears higher (16 percent on average) than uptake into the nonwage sector (7 percent). The nonparametric hazards suggest that a smooth functional form with monotonic increasing or decreasing duration dependence, such as the commonly used Weibull distribution, may severely restrict the movement of the underlying hazard. Thus, the hazard's flexible form seems appropriate.

Table 2 presents the means and standard deviations of covariates included in the model. Note that women make up 20.4 percent of redeployees in the sample and that exits are roughly evenly divided before and during or after 1987. The predicted premium for wage-sector employment is developed from wage and nonwage earnings expressions that are based on data from 2,565 individuals working in Conakry. A full-switching regression system, including the wage-equation estimates used to generate the premium variable, is presented in Appendix 2. For a description of the estimate of the switching regression system, see Mills and Sahn (1993).

The wage premium is calculated as the logarithm of predicted wage earnings minus the logarithm of predicted nonwage earnings based on the earnings expression parameters and the redeployee's individual characteristics. Although the predicted wage premium is negative for all redeployees in the sample, almost all redeployees indicated in discussions that the wage sector was the preferred type of employment. This suggests significant nonmonetary benefits may accrue to wage-sector employment. If these benefits are positively correlated with observed wage earnings, the premium variable will still provide a good approximation of the relative preferences attached to wage employment.

¹² The estimated state specific hazard rates do not sum to the estimated total hazard rate because, for each hazard, departures to the other state within the period are treated as censored.

Figure 2 - Nonparametric Hazard Rates from Unemployment to Wage and Nonwage Employment

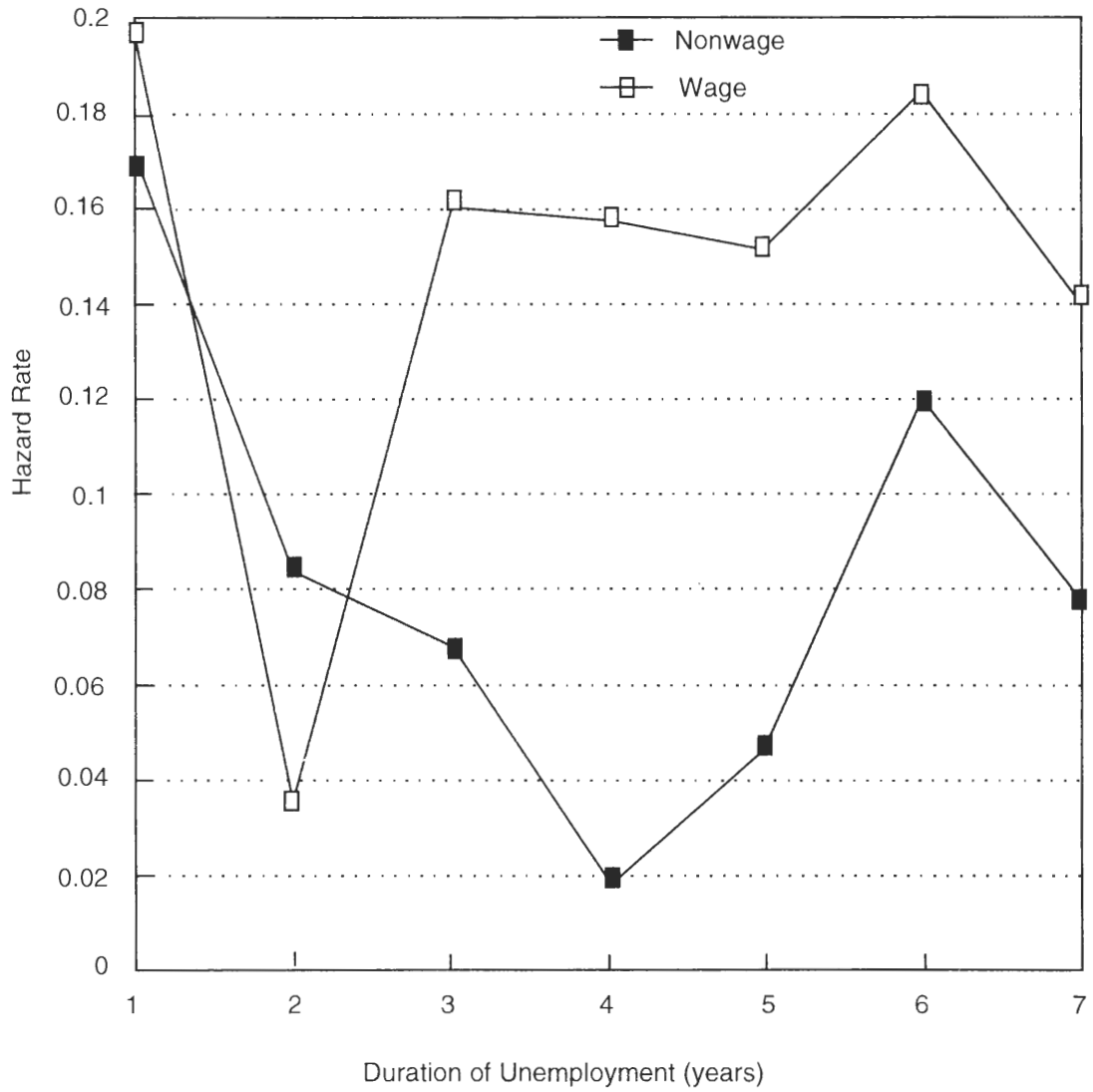


Table 2 — Summary Statistics for Redeployed Public Sector Workers in Conakry, Guinea (n=152)

Variable	Description	Mean	Standard Deviation
Gender	Female = 1	0.204	0.404
Age	Age in years at departure of public sector	43.416	10.207
Left 87	Left public sector in, or after, 1987 = 1	0.461	0.500
Sev	Received severance benefits after departure = 1	0.375	0.486
Premium	Predicted ln (wage earnings) minus predicted ln (non-wage earnings)	-0.792	0.317

5. RESULTS

The covariate parameter estimates for both single- and dual-risk models are presented in Table 3. Since covariates are included in the original hazard specification as $-X_i\beta$, a positive parameter estimate implies a decrease in the probability of departure from unemployment in each period or, correspondingly, an increase in the duration of unemployment. For example, in the single-risk case the parameter estimate for the female dummy variable is negative, implying that being female is positively related to the probability of departure from unemployment in each period. On the other hand, receipt of severance compensation payments and the size of the wage-sector premium are negatively correlated to the probability of departure from unemployment. Finally, age and whether departure from the public sector occurred in or after 1987 are estimated to have no significant impact on the probability of departing unemployment in the single-risk case.

For the dual-risk estimator, the parameter estimate for female departures into the wage sector is not significant. However, female redeployees have a significantly higher probability of leaving unemployment for the nonwage sector in any period. The impact of severance pay appears to be concentrated in the wage sector and the parameter estimate suggests that individuals who receive severance compensation are less likely to enter the wage sector in any period than those who do not. The parameter estimates for the age, departure date, and wage-premium variables in both the wage- and nonwage-sector equations are not significant. The parameter estimates for the wage-premium variable are positive in both exit states and are of roughly the same magnitude as the estimates for the single-risk premium variable. Finally, the covariance parameter estimate is positive but non-significant. This is not surprising since Sueyoshi (1992), based on Monte Carlo results, suggests that reasonable covariate estimates are obtained in moderately small samples but that more than 500 observations are needed for an accurate approximation of the covariance parameter.

The estimated baseline hazards for all departures, as well as separate wage- and nonwage-sector departures, are presented graphically in Figure 3. The baseline hazard for all departures is fairly flat across periods similar to those of its nonparametric counterpart in Figure 1. However, the estimated hazard rates for departures from unemployment are lower due to the presence of covariates. Correspondingly, the wage and nonwage baseline hazards show essentially the same pattern as the nonparametric estimates in Figure 2, but are again smaller due to the presence of covariates. Thus, as suggested by the model, the presence of covariates does not appear to change the estimated form of the underlying hazard.

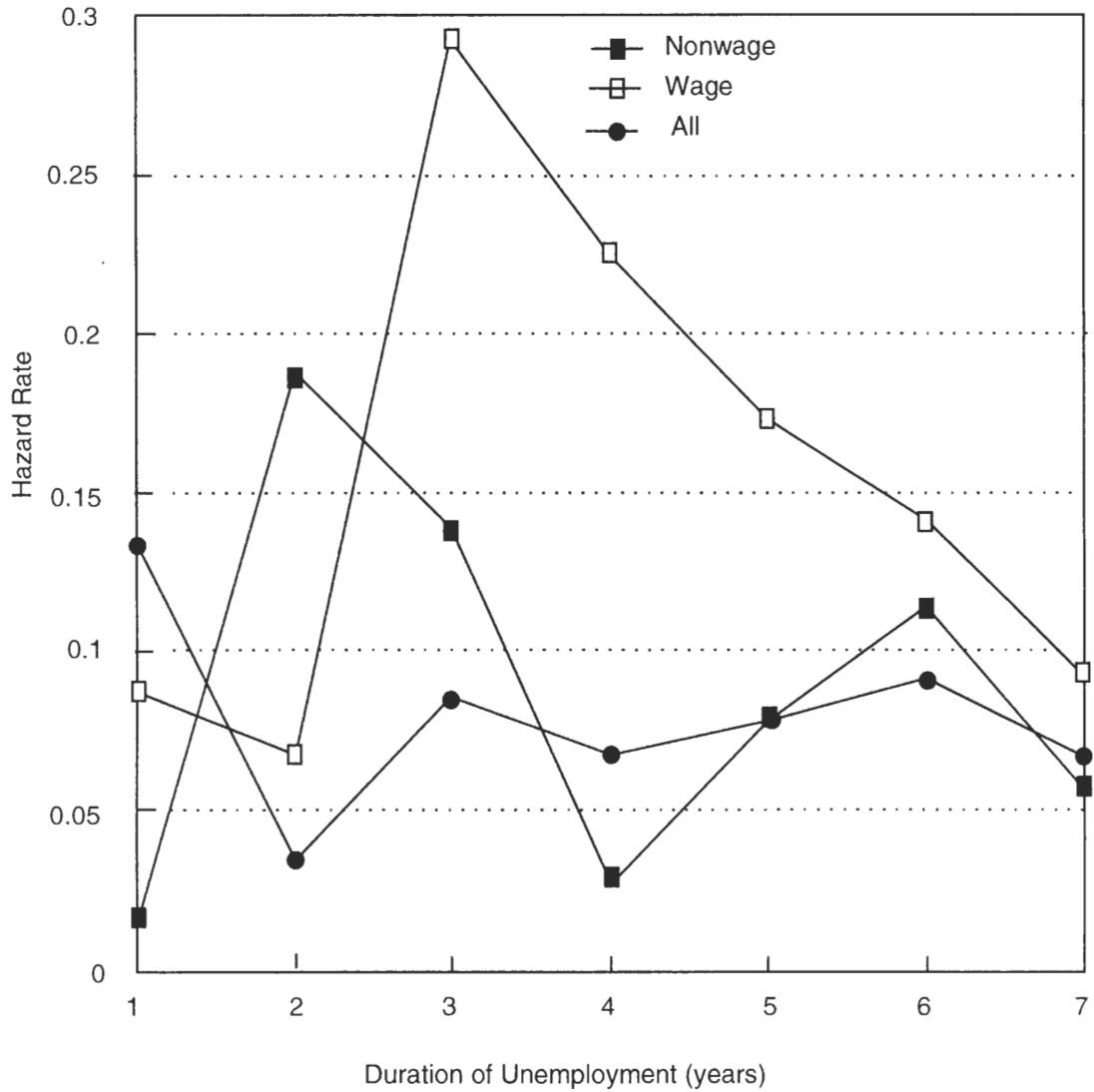
Table 3 — Covariate Parameter Estimates for the Single- and Dual-Risk Models

	Single Risk		Dual Risk			
	All		Wage Sector		Nonwage Sector	
	Parameter Estimate	t-Statistic	Parameter Estimate	t-Statistic	Parameter Estimate	t-Statistic
Gender	-0.6641	-1.81*	0.0966	0.16	-1.0309	-2.63**
Age	-0.0060	-0.50	0.0053	0.38	-0.0119	-0.75
Left 87	-0.2033	-0.97	-0.4799	-1.49	0.5189	1.48
Sev	0.7169	3.09**	0.8884	3.64**	0.2311	0.53
Premium	0.9701	2.09**	0.8727	1.56	0.6732	1.37
Rho			0.2853	0.13		
Log likelihood	-250.09		-299.03			

* Significant at the 0.10 Level.

** Significant at the 0.05 Level.

Figure 3 - Stepwise Approximation of the Baseline Hazard Functions for the Single- and Dual-Risk Models



6. DISCUSSION

In general the results support the hypotheses generated by the model and highlight the importance of modeling wage and nonwage departures from unemployment as separate exit states. The single exit state model suggests females are 1.94 times more likely than males to leave unemployment in any period. In the standard job-search model, this would lead to the erroneous conclusion that females were receiving employment offers at a higher rate than their male counterparts.

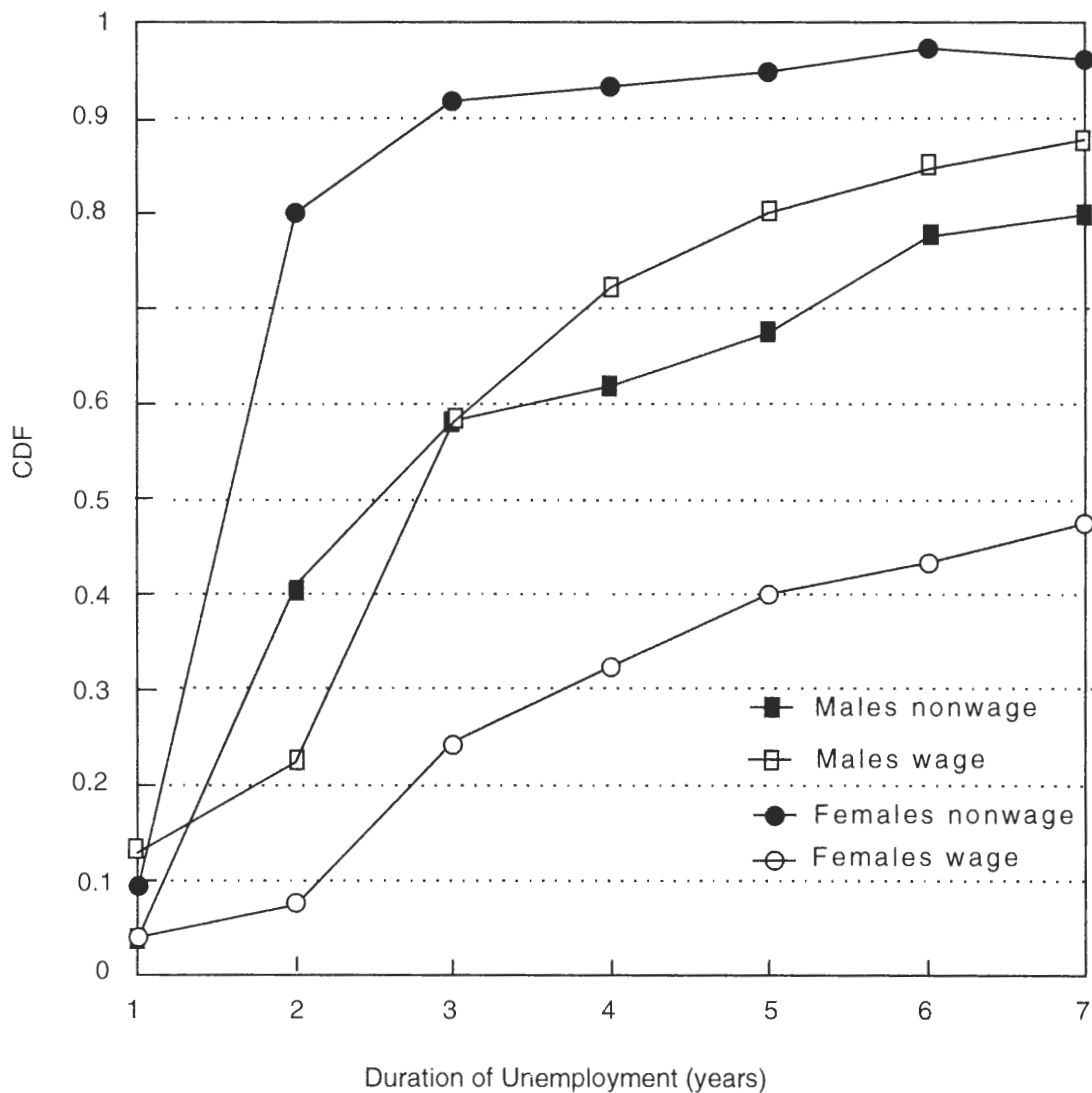
However, the separation of exits to the wage and nonwage sectors makes it clear that the higher rate of unemployment departure among females is driven by the nonwage sector, which females are 2.80 times as likely as males to enter in any period. Based on the covariate and baseline hazard estimates, the cumulative density functions for male and female departures to the wage and nonwage sectors are calculated from the average characteristics of the two groups (Figure 4). In the absence of wage sector exits, over 90 percent of females are predicted to exit unemployment into nonwage employment within three years of departure from the public sector. The comparable figure for males is 59 percent. However, for wage-sector exits, only 24 percent of females exit within three years versus 58 percent of males. Since the nonwage sector is generally assumed to be the less preferred sector of employment, the results support the model's premise that females, realizing their poor prospects in the wage sector, are more inclined to accept more readily available, but less preferred, nonwage employment.¹³

The concentration of the impact of severance payments in the wage sector also conforms with the results of the model. Individuals receiving severance payments exit to the wage sector at only 0.41 times the rate of those not receiving severance payments. However, no impact from severance payments is measured in the nonwage sector, supporting the assertion that severance payments may provide countervailing incentives and disincentives to acceptance of nonwage employment. Further, the size of the premium for wage-sector employment is negatively related to the probability of exit from unemployment in the single-risk case and yields similar, but insignificant, parameter estimates for both the wage and nonwage sectors. Given the sample size, these results do not provide a strong rejection of the hypothesis that the differential in expected earnings between sectors plays an important role in job-search strategies.

By contrast, the estimated coefficients for the impact of age on the probabilities of accepting wage and nonwage employment do not support the hypotheses generated by the search model with rationed wage-sector employment. However, it should be noted that in correspondence with the theoretical expectations of the model, many elderly redeployees decided not to search for new

¹³ It should also be noted that the specification of the model restricts gender to have a constant proportional impact on the hazard rates out of unemployment. An alternative test of gender discrimination would estimate separate dual-hazard functions for males and females and compare the magnitudes of the baseline hazards. Unfortunately, the limited sample size makes this alternative specification of the model impossible to test.

Figure 4 - Calculated Cumulative Distribution Functions (CDF) for Male and Female Departures from Unemployment



employment and were not included in the sample. Thus, the age parameter estimates are weak measures of the applicability of the model.

7. CONCLUSIONS

This paper highlights the complex nature of job-search behavior in a segmented labor market. Transitional unemployment after public-sector retrenchment is a cost of public-sector employment-reduction programs that is particularly worrisome to politicians. However, transitional unemployment is also an important component of optimal job-search strategies. In a segmented labor market with rationing of preferred wage-sector positions, the increased likelihood of obtaining a preferred position is often correlated with a longer duration of unemployment. Hence, groups that experience discrimination in the wage sector, such as females, experience shorter durations of unemployment following job loss. But these groups remain relatively disadvantaged by their restricted access to superior employment opportunities. This implies that the cost to displaced workers of public-sector retrenchment can not be inferred from the duration of unemployment alone, but only in conjunction with a comparison of earnings in newly obtained employment and in the previous public-sector position. Unfortunately, a careful comparison of pre- and post-retrenchment earnings is not possible with the current data set. Pre- and post-retrenchment earnings should be examined in future analyses of the human costs of redeployment programs.

On the basis of unemployment durations and changes in earnings, the cost of gender discrimination should be addressed during the design and implementation of retrenchment programs. Severance payments can be calibrated to cover the additional losses from discrimination that workers face in the private sector. Quotas can be established to limit the redeployment of workers who would face discrimination in the private sector. Many governments may be hesitant to establish policies that give explicit preferences to certain groups of public sector workers.

It may be most effective to reduce the costs of discrimination by providing workers who will face discrimination in the private sector with additional assistance in obtaining nonwage employment opportunities that yield higher returns. While severance payments, if properly disbursed, can be particularly important in relieving capital constraints to nonwage employment opportunities, additional assistance in identifying enterprise opportunities and developing entrepreneurial skills could also be provided to women and other target groups.

REFERENCES

- Akerloff, G. 1984. *An Economic Theorist's Book of Tales*. New York: Cambridge University Press.
- Cox, D. 1975. "Partial Likelihood." *Biometrika*. 62: 269-276.
- Diamond, P. and J. Hausman. 1984. "The Retirement and Unemployment Behavior of Older Men." In *Retirement and Economic Behavior*. Edited by H. Aron and G. Burtless. Washington, DC: Brookings Institute.
- Han, A., and J. Hausman. 1990. "Flexible Parametric Estimation of Duration and Competing Risk Models." *Journal of Applied Econometrics*. 5: 1-28.
- Katz, L. 1986. "Layoffs, Recall, and the Duration of Unemployment." Working Paper 1825. Cambridge: NBER.
- Lancaster, T. 1990. *The Econometric Analysis of Transition Data*. New York: Cambridge University Press.
- Lippman, S., and J. McCall. 1976. "The Economics of Job Search." *Economic Inquiry*. 14: 155-189.
- Mills, B., and D. Sahn. 1993. "Is There Life After Public Service: The Fate of Retrenched Workers in Conakry, Guinea." Cornell Food and Nutrition Policy Program Working Paper. Ithaca, NY: CFNPP.
- Sueyoshi, G. T. 1992. "Semiparametric Proportional Hazards Estimation of Competing Risk Models with Time-Varying Covariates." *Journal of Econometrics*: 25-58.

APPENDIX 1

Proposition: If it is optimal to search for wage employment in period T , it is optimal to search in period $T-1$.

Proof: Assuming it is optimal to search in period T , the expected value from search in T is greater than the expected returns from nonwage employment and non-participation:

$$\lambda \int_0^{\infty} w_T f(w_T) dw_T > E[s_T]. \quad (\text{A.1})$$

In period $T-1$ it is also optimal to search if the expected value from search in $T-1$ is greater than the expected returns to nonwage employment and non-participation in $T-1$:

$$\lambda \int_{H'}^{\infty} (1 + \delta) w_{T-1} f(w_{T-1}) d(w_{T-1}) * \quad (\text{A.2})$$

$$\left[1 - \lambda \int_{H'}^{\infty} f(w_{T-1}) dw_{T-1} \right] \delta \lambda \int_0^{\infty} w_T f(w_T) dw_T > \xi_{T-1};$$

where

$$H' = \delta / (1 + \delta) \lambda \int_0^{\infty} w_T f(w_T) dw_T.$$

The expected returns to wage employment, nonwage employment and non-participation remain the same each time period, so that

$$E[w_{T-1}] = E[w_T] \text{ and } \xi_{\mu_{T-1}} = (1 + \delta) \xi_{\mu_T}.$$

Then:

$$\begin{aligned} & (1 + \delta) E[w_T] - (1 + \delta) \lambda \int_{H'}^{\infty} w_{T-1} f(w_{T-1}) dw_{T-1} \\ & + \left[1 - \lambda \int_{H'}^{\infty} f(w_{T-1}) dw_{T-1} \right] \delta \lambda \int_0^{\infty} w_T f(w_T) dw_T \\ & > (1 + \delta) \xi_T. \end{aligned} \quad (\text{A.3})$$

Clearly the expected returns from searching in period $T-1$ must be greater than the returns of the next best option if:

$$\begin{aligned} & \left[1 - \lambda \int_{H'}^{\infty} f(w_{T-1}) dw_{T-1} \right] \delta \lambda \int_0^{\infty} w_T f(w_T) dw_T \\ & \geq (1 + \delta) \lambda \int_0^{H'} w_{T-1} f(w_{T-1}) dw_{T-1}. \end{aligned} \tag{A.4}$$

Evaluating the integrals in (A.4):

$$\begin{aligned} & [1 - \lambda [1 - F((\delta/1 + \delta) \lambda E[w_T])]] \delta \lambda [E w_T] \\ & \geq (1 + \delta) \lambda \left[(\delta/1 + \delta) \lambda E[w_T] F((\delta/1 + \delta) \lambda E[w_T]) - \int_0^{H'} F(w_{T-1}) dw_{T-1} \right] \end{aligned} \tag{A.5}$$

or

$$(1 - \lambda) (\delta / 1 + \delta) E[w_T] \geq - \int_0^{H'} f(w_{T-1}) d(w_{T-1}).$$

This condition must hold since $F(w_{T-1}) \geq 0$ for all $w_{T-1} \geq 0$. By extension to the multi-period model, the expected returns from search decreases faster over time than the expected returns of nonwage employment and non-participation.

Appendix 2 – Earnings and Switching Equation Estimates from a Switching Regression System of Equations

	Dependent variable: In (hourly earnings)				Dependent Variable: Wage Sector = 1	
	Wage Sector		Nonwage Sector		Parameter Estimate	t-Statistic
	Parameter Estimate	t-Statistic	Parameter Estimate	t-Statistic		
Intercept	4.3808	(16.243)	4.4033	(10.56)**	-0.2063	(-1.49)
Age	0.04544	(3.89)**	0.0795	(4.63)**	0.0093	(2.80)**
(Age) ²	-0.0005	(-3.61)**	-0.0009	(-4.26)**		
Gender (female = 1)	-0.854	(-0.74)	-0.4979	(-2.84)	-1.1563	(-15.30)**
Education						
Primary	0.1541	(1.57)	0.1333	(0.83)	0.7663	(10.36)**
Secondary	0.2687	(1.84)*	0.1946	(0.59)	1.4723	(14.75)**
University	0.5817	(3.56)**	0.8339	(1.75)*	1.8980	(14.58)**
Literate	0.1349	(2.26)**	0.3145	(2.68)**		
No. primary men					-0.0442	(-1.66)**
No. secondary men					0.0563	(1.09)
No. university men					0.2210	(2.29)**
No. primary women					0.0357	0.87
No. secondary women					0.1584	(2.04)**
No. university women					0.0797	(0.48)
Duration last employment	0.0093	(3.96)**	0.0163	(3.85)**		
Ethnicity						
Fulani	-0.0163	(-0.36)	-0.0865	(-1.10)	-0.2342	(-3.11)**
Malinke	-0.0579	(-1.25)	0.1513	(1.77)*	-0.1310	(-1.58)
Forester	0.0545	(0.73)	0.3509	(2.79)**	-0.0682	(-0.56)
Quarter (1st = 0)						
2nd	0.0651	(1.38)	-0.1109	(-1.44)		
3rd	0.1808	(3.99)**	-0.3211	(-3.83)**		
4th	0.0338	(0.68)	-0.4739	(-5.50)**		
Redeployee	0.1876	(2.23)**	0.4180	(1.69)*	0.0547	(0.37)
Capital (1,000,000)			0.1600	(11.24)**		
Center City					-0.1369	(-1.48)
Married					-0.0762	(-0.95)
No. children < 6					-0.0454	(-1.97)**
No. children <1 ≤, ≥6					-0.0180	(-0.89)
σ _{ww}	0.5956	(51.86)**				
σ _{ss}	1.0309	(59.63)**				
ρ _{sv}	-0.0678	(-0.24)				
ρ _{sv}	-0.0370	(-0.14)				
Log likelihood	-4267.97					
No. of individuals	2565					

* Significant at 0.10 level.
 ** Significant at 0.05 level.